CASOS

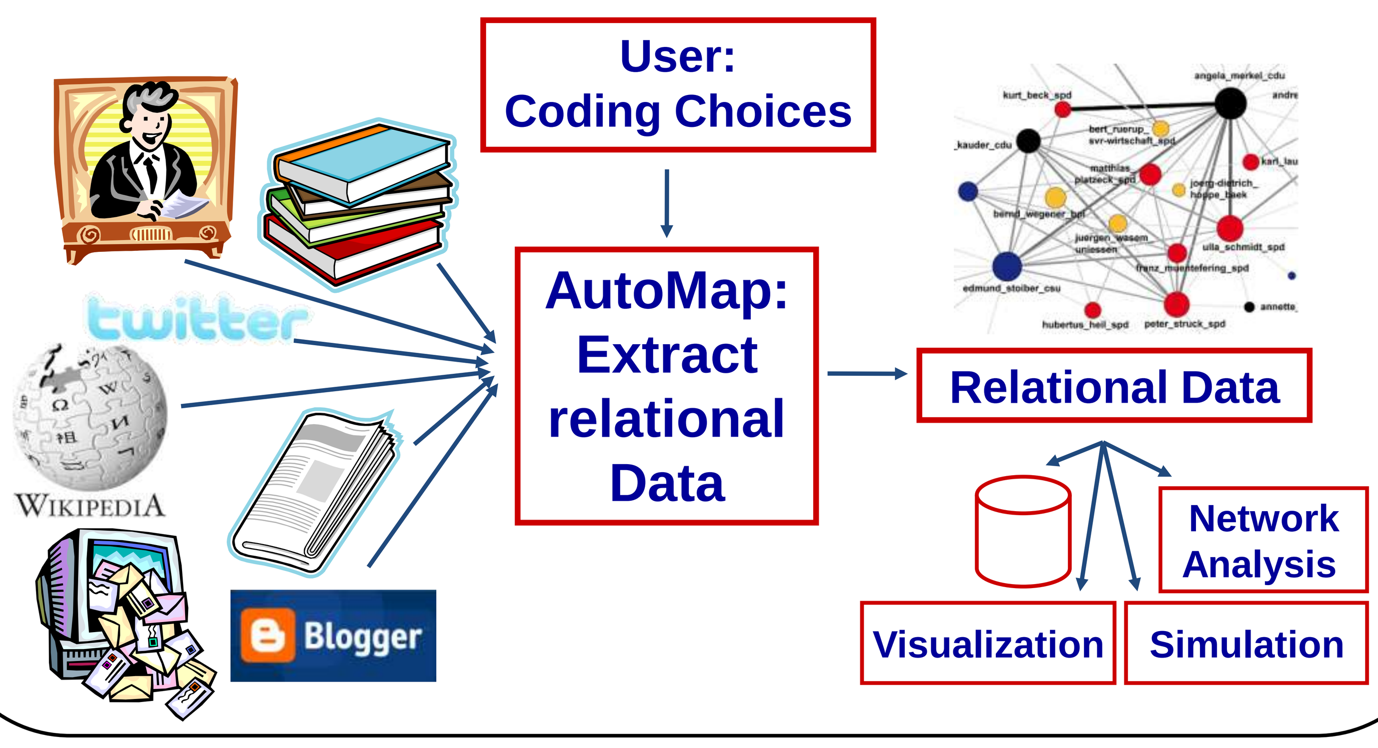
Carnegie Mellon

Ph.D. Program in Computation, Organizations & Society

From Texts to Networks

Jana Diesner
diesner@cs.cmu.edu

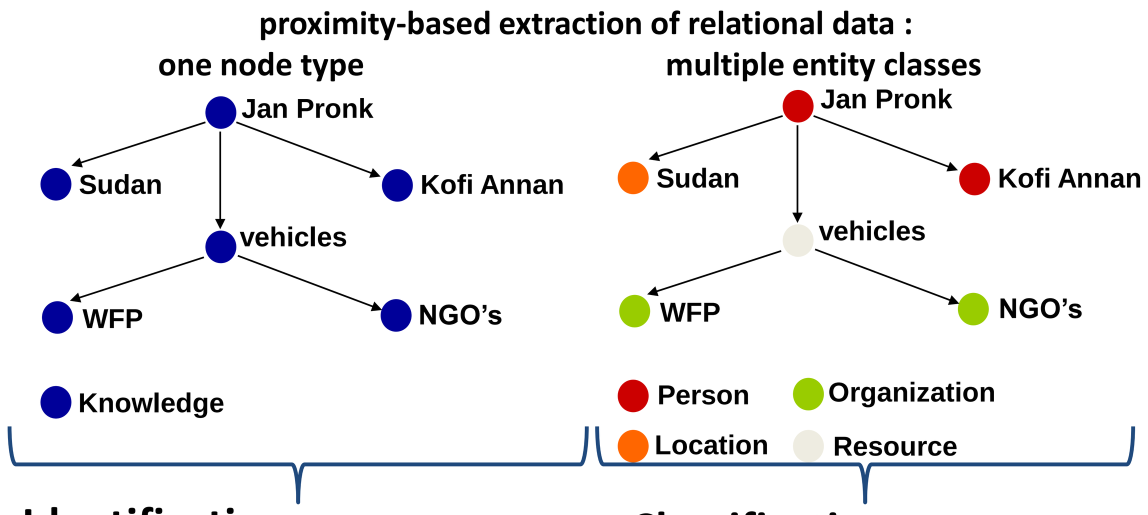
Prof. Kathleen M. Carley
kathleen.carley@cs.cmu.edu



Illustrative Toy Example:

"Jan Pronk, the Special Representative of Secretary-General Kofi Annan to Sudan, today called for the immediate return of the vehicles to World Food Programme (WFP) and NGOs." (from UN News Service, New York, 12-28-2004):

proximity-based extraction of relational data :

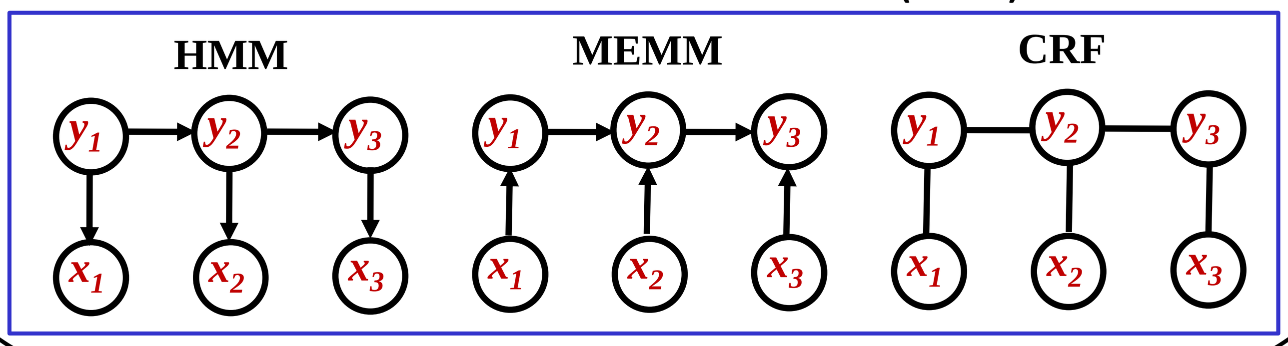


Identification:
For relational data with at least one node type: **Locate/ identify** relevant nodes (may be multi-word units)

Classification:
For ontologically coded networks: **Classify** relevant nodes according to an ontology or taxonomy

Development of Computational Solutions

- Utilize machinery from Machine Learning and Artificial Intelligence
- Deploy and develop supervised and semi-supervised **sequential stochastic learning techniques** in order to train classifiers and build models that generalize to new data
- Construct a classifier *h* that for every sequence of ***(x, y)*** (joint probability) (where *x* = words per sequence and *y* = corresponding category) or ***(x|y)*** (conditional probability) predicts a sequence ***y = h (x)*** for any sequence of *x*, incl. new and unseen data
- We work with Generative (aka discriminative) models: *P(x,y),* such as Hidden Markov Model (HMM), and Conditional models: *P(y|x)*, such as Maximum Entropy Markov Models (MEMM) and Conditional Random Fields (CRF)



Natural Language Processing and Relational Data Extraction Routines in AutoMap

- **Stemming**: Converts words into their morphemes.
- **Reduction and Normalization**:
  - Negative filters such as delete lists, removal of symbols and formatting, removal of numbers
  - Positive filters such as thesauri, spelling correction, synonym sets, antonym sets
- **Part of Speech Tagging**: Assigns a single best grammar classifier or lexical category to every word.
- **Anaphora Resolution**: Converts personal pronouns into the entity or entities that the pronouns refer to.
- **Named Entity Extraction**: Identifies relevant types of information that are referred to by a name, such as people, organizations, and locations.
- **Ontological Text Coding**: Classifies relevant types of information according to an ontology or taxonomy. User-defined categorization schemata can be applied.
- Identification of and reasoning about **node and edge attributes**, such as demographic data, beliefs, and types of relationships.
- **Email Data Analysis**: Extracts and combines different types of networks, such as social networks and knowledge networks, from emails.
- **Feature Identification**: e.g. term weights, TF*IDF
- **Entropy Assessment**: Determines the variability or heterogeneity of a text document or corpus with respect to its vocabulary.
- Classical **Content Analysis**.
- Read and write data and processing material from and to a default or user-specified **database**.

Example: Conditional Random Fields for Entity Extraction and Ontological Text Coding

- Identify and classify words that represent instances of entity classes of models or ontologies that **deviate** from classical set of Named Entities.
- Crucial step for coding texts as social-technical networks according to domain-specific ontologies and for advanced modeling of complex and dynamic real-world organizations or networks.
- Model relationship among y_i and y_{i-1} as Markov Random Field conditioned on *x*
- Conditional distribution of entity sequence *y* given observation sequence *x* computed as normalized product of potential functions $M_{i:}$

$$M_i(y_{i-1}, y \mid x) = (\exp\left(\sum_\alpha \lambda_\alpha f_\alpha(y_{i-1}, y_i, x) + \sum_\beta \mu_\beta g_\beta(y_i, x)\right)$$

$$p_\theta(y \mid x) = \frac{\prod_{t=1}^{n+1} M_i(y_{i-1}, {}_{yi} \mid x)}{\prod_{i=1}^{n+1} M_i(x)_{start\ ,stop}}$$

- Conditional probability of label sequence *P(y|x)*, where both *x* and *y* are arbitrarily long vectors (consider arbitrarily large bag of features (> 10,000) and any property of *x*, such as long-distance information)

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